Optimizing The Dock Selection Process And Measuring Manpower Productivity For Single Order Picking Process In A Warehouse: A Case Study Of A FMCG Company In India

Omkar Kad[1], Paluri Achuta Ratna[2*]
[1] Symbiosis Institute of Operations Management, Nashik, Symbiosis International (Deemed University), Pune, India
[2] Associate Professor, Symbiosis Institute of Operations Management, Nashik, Symbiosis International (Deemed University), Pune, India
*E-mail: kad.omkar@siom.in

ABSTRACT

Warehouse operating costs are a major component of the supply chain costs. Manpower cost and in particular the picking cost contributes substantially to the warehouse operating cost. Optimizing the picking process and tracking workforce productivity at the granular level is the key to reducing costs. Organizations follow different picking processes based on criteria such as frequency of the customer order, strategy used for fulfilling customer orders and so on. This study focuses on the low-level single order picking process. Time taken for picking a particular customer order is dependent on dock selected for staging area. A case study of a FMCG company was used for the purpose of analyzing the productivity for single order picking process in a warehouse. A VBA based MS-excel tool was created to predict the optimized dock and measure the productivity of workforce. This lead to an increased picking process efficiency. Input to VBA based MS-Excel tool were warehouse order which had information related to the picklist and pallet fit ratio. The output of tool were the 3 top docks for staging along with time required for picking at the recommended dock. Algorithm used for this tool was dynamic and it could predict standard time required for picking a particular customer order thus helping in measuring the performance efficiency and productivity.

Keywords

Order picking, low level picking, optimization, dock selection process, staging, coefficient of variation, uniform distribution, standard time, pallet break

Introduction

Order picking which is the process of selecting a set of items, retrieving them from storage bins and transporting them to consolidation/staging area for order fulfillment (Rouwenhorst et al., 2000), is one of the most expensive activity because it is labor and capital intensive activity (Frazelle, 2002). Around 55% of the total cost in warehouse operation is contributed by picking activity (Bottani, Montanari, Rinaldi, & Vignali, 2015; Tompkins et al., 1996). Majority of time invested in picking activity comprised of time taken for travelling (Yen, 1970). Time taken for travelling can be minimized by optimized traveling distance (Brezina and Cickova, 2011; Colorni et al., 1991). Staging area selection which refers to the selection of an area close to an outbound dock to store picked goods, plays an important role in reduction of traveling distance. Thus, to reduce travelling distance, most optimize dock should be selected for a particular warehouse order for single order picking. Manpower productivity is measured using a formula across industry. Karim (2020) benchmarked a ratio-based productivity formula. Measuring productivity is a great challenge if productivity standards are established as per large facilities which had economies of scale advantage. A rational method to measure productivity of a manpower accurately is need of most warehouses. A wrist band was used to measure productivity (Hwang & Lee, 2017) in various warehouse operations.

Precise routing algorithms are only available for a limited set of warehouse layouts. Stretching the exact approaches to the case of a more complex warehouse is nontrivial, and in any case, the computation times increase rapidly when more than two blocks need to be evaluated (Roodbergen & de Koster, 2001; Theys et al., 2010). The complexity of the TSP increased with the number of items in the picking list (Scholz et al., 2016). Consequently, researchers proposed heuristic algorithms to route order pickers in complex scenarios. This indicated the need for new algorithms that are viable for distribution center

arrangements with multiple blocks, from the perspective of both arrangement quality and computational execution. Floyd-Warshall computation algorithm (Santis et al., 2017) introduced the shortest path calculation by calculating shortest distance between 2 nodes but failed to explain the most optimize dock if the customer order quantity is large enough to pick in one trip. So, if 2 or more trips are needed to pick the picking list then this method fails. Thus, a need was felt to study the optimum distance covered by a picker where multiple circular trips were covered and measure productivity of manpower.
Existing literature suggested models which were based on heuristics (Maknoon and Baptiste,2009). Moreover, all these models were static in nature and focused more on warehouse layout design (Önüt et al., 2008; Roodbergen, Vis and Taylor 2015). The simulation model available for distance minimization was expensive to implement (M Bučková., 2017). Moreover, available models focus more on batch and zone picking. Thus, a gap was identified to create a model which captured all factors that increased the granularity of the model to minimize the travelling distance and predict standard time accurately in picking. Thus, a model was needed which should be dynamic in nature and can be implemented on ground for single order picking. Based on the literature reviewed, it can be inferred that there are studies on understanding factors that impact optimization but few studies implemented all factors in their model to create a dynamic model to optimize dock selection process. Therefore, this is potential area with the scope of understanding and determining the granularity/detail level involved in picking process and to identify granular factors that could optimize route of a picker in order picking. This study speaks of a VBA based MS-Excel model which optimized and automated dock selection process for single order picking. Warehouse order range from a 1-line item with high lot size to many lines item with few orders quantity per line item. Thus, for such high level of dynamics involved, a dynamic model was required to automate productivity tracking and optimize dock selection process.

1.2. Objective of this research

Objective of this study is to develop a dynamic model which can optimize the dock selection process in a low-level picking warehouse. This model considered granular and dynamic factors that increased its granularity/detail level to predict result accurately. This suggested model should also enable us to predict standard time required for picking a warehouse order, so that this standard could be compared with actual timings to analyze performance efficiency and manpower productivity.
The remaining of this paper is organized as follows. In section 2, a literature review on optimization of order picking and productivity measuring tools is presented. Section 3 deals with the data collection, section 4 presents the case of the FMCG company followed by an analysis of data and decision on assumption used in calculating standard time. In section 5, the developed model is applied in warehouse to optimize picking efficiency. In Section 6 managerial insights are discussed.

Literature Review

Measuring productivity and optimizing manual low level order picking required careful consideration of structural aspects (Celik & Sural,2018), planning problems (Yu & De koster,2009) and interdependencies between this factor. In dynamic picking condition (Bukchin et al., 2012), variable selection impacted optimization and productivity. There is trade-off within these variables. Optimized values of variables improved efficiency. Warehouse layout played an important role in improving the productivity and efficiency of workforce. A particle swarm optimization algorithm for the multiple-level warehouse layout (Önüt et al., 2008) prescribed the method to design warehouse to increase productivity of warehouse. Layout optimization of a three-dimensional order picking warehouse (Rakesh et al., 2015) provided the impact of warehouse layout on overall capacity and responsiveness of a warehouse. Roodbergen, Vis and Taylor (2015) integrated the warehouse layout in a model and showed through simulation how this can help to improve productivity and capacity of a warehouse.
Capacity pipeline of warehouse facility is decided by a picking method (Gwynne Richards, 2017).

Picking method selection depends on manpower allocated for picking against total dispatch. In this study low-level single order picking method is analyzed. Batch picking and zone picking increased the picking efficiency and warehouse throughput but it impacts responsiveness (Ashayeri et al., 1985). Routing means determining the routes of the pickers through travelling salesman problem while retrieving the picking items. Optimal routing problem for conventional warehouse with one cross-aisle were available. An exact algorithm for solving the TSP existed for rectangular warehouses, which only had crossovers at the ends of the aisles (Ratliff & Rosenthal (1983). De Koster and Van der Poort (1998) had proposed a polynomial algorithm for 1 block warehouse. Total number of SKU's in a FMCG industry warehouse were very high. To pick warehouse order with a load of more than full truck load, picker had to start picking with first pallet, break that pallet at a suitable point and then carry this SKU cases/boxes loaded pallet to dock for staging. Thus, performance of picker depends on the point where he breaks the pallet. Huurne (2016) proposed a method to optimize pallet break down process for SCANIA. Travelling time was reduced if pallet is filled more than 100% utilization but it impacts visibility and accuracy. As per Gwynne Richards (2017), accident and traffic congestion in aisles increased by 50% if pickers load pallet above 100% utilization. Effect of load and speed on the cost of human walking (Bastien et al., 2005) showed human walking speed decreased when human carried load and this decrease in speed was proportional to load carried. Speed decreased varied from human to human.

Most studies consider only single receiving door and single shipping door (Yu and Egbelu,2008; Maknoon and Baptiste,2009; Forouharfard and Zandeih, 2010; Boysen et al., 2010; Vahdani and Zandeih, 2010; Soltani and Sadjadi, 2010; Arabani et al.,2011) De Koster and Van der Poort (1998) additionally proposed a polynomial algorithm for a 1-block distribution center, broadening that made by Ratliff and Rosenthal (1983) to tackle the directing issue for a non-focal area of the warehouse. Ants colonies optimization was presented (Dorigo et al., 1991; Dorigo et al., 1996;) as a probabilistic method for tackling computational Programs. ACO was propelled by genuine ants' provinces: while moving ants leave pheromone on the ground, hence making the way. ACO was regularly received to take care of enhancement issues where the objective was to distinguish the most limited way and has been applied to this conclusion to unravel the TSP, both in its conventional plan (Brezina and Cickova, 2011; Colorni et al., 1991) and the MAX-MIN framework variation (Shtovba, 2005; Stutzle and Hoos, 2000). In addition, ACO has been received in a wide range of building fields (De Jong and Wiering, 2001; Lucic, 2002; Mariano and Morales, 1999), recommending different zones of use. Computer simulation (M Bučková., 2017) optimized transport distance in warehouse using simulation software Tecnomatix Plant simulation 13 software. Tecnomatix plant simulation 13 software optimized distance covered by a picker in multiple circular trips, but the simulation package was costlier and thus very few firms and institution are using it. It had been identified that using a similar working principle a VBA code can be written in a MS-Excel to identify all possible routes to pick a picklist and shortest among them could be used to identify most optimize dock.

Methodology

3.1 Sources of data

Both Primary as well as secondary data were required for this study. Secondary data was obtained through online sites, research reports, books, journals and news article. Primary data was collected through Time motion study. The study was conducted in warehouse for an FMCG major from May 2010 to July 2010. Studied warehouse was located in Bhiwandi in Mumbai, India. The monthly turnover of this warehouse was around 18000 full truck loads. Primary data was collected by observing 7 pickers in the warehouse for a period of 2 months. Time Motion Study was conducted in warehouse layout shown in Figure 1.

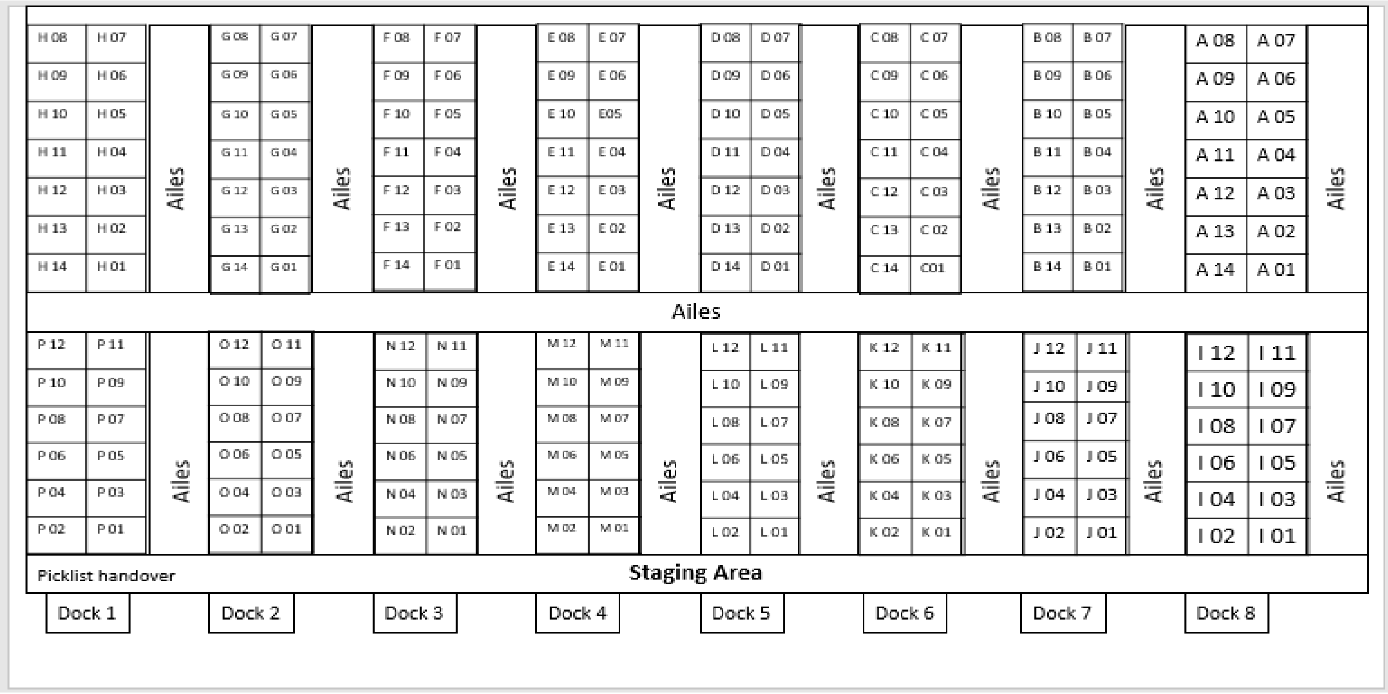


Figure 1: Warehouse layout with 2 blocks

3.2 Sample Size

In order to determine the appropriate sample size, following formula was used

$$Sample\ size = \frac{\frac{z^2 * p(1-p)}{e^2}}{1 + \frac{z^2 * p(1-p)}{e^2 N}} \qquad \mathbf{(1)}$$

Assumptions considered for calculating sample size are presented in Table 1.

Table 1: Sample Size Calculation

Population Size (N)	527850
Confidence level	99%
Margin of error I	10%
Z-score @ 95% (z)	1.96
Percentage value (p)	5%
Sample Size in warehouse orders	30
Number of Pickers	7

Details of population size are shown in Table 2.

Table 2: Population size calculation

Cities	**Population**
Average warehouse orders in a month	44010
Total no of months	12
Total	**5,27,850**

3.3 Methods used for data analysis

All above mentioned data was collected from an FMCG company, to establish standards and calculate productivity of workforce/manpower. Thus, it was important to analyze data correctly without any mistakes. For human walking speed and cutoff utilization, basic statistics like mean, median and mode along with coefficient of variation were used. For pallet formation descriptive statistics was used to identify correct time required for pallet formation.

The case of a FMCG company

In a consumer commodity warehouse majority of operating expenses was invested in Workforce. Thus, to track and optimize this cost, a need was felt to optimize the dock selection process for a low-level single order picking process of warehouse operation. There are 4 major activities carried out in every warehouse. These activities were: - Unloading, allocation, picking and loading. Unloading and allocation activities consist of inbound warehouse operation while picking and loading consists of outbound activity. Unloading activity starts as fleet is arrived. Documents like lorry number and lorry details were checked by security guards to confirm the fleet. Once documents were checked then vehicle is parked at a suitable dock, security guard opened the seal of vehicle and unloading process is initiated. In unloading process workforce unloads the case of a SKU and forms a pallet of the same SKU. The quantity of SKU stacked on a pallet is determined by pallet fit for a SKU. Post pallet was formed it was carried to staging area. Post unloading, the next operation was to conduct ERP transaction for receiving goods in ERP system. Once goods are received, next step was to allocate these goods to designated Bins. In a warehouse management system i.e., WMS enabled warehouse, allocation was suggested by an ERP platform. In non-WMS enable warehouse, allocation was suggested manually on the basis of available empty bins. Allocation is scheduled for implementation. While implementing workforce used hand operated pallet truck or battery-operated pallet truck to pick a pallet and carry it towards designated bin. Depending upon bin location in rack, stacker is used to pick that pallet and keep it in the designated rack. Inbound operations end here. Outbound operation was initiated with a customer order or order from marketing and sales team. Customer order was handed over to picker- a workforce assigned for picking activity. Picking can be done through various ways but in this study single order picking is analyzed. In single order picking, a picker takes a single customer order at time and proceeds for it. Picker's next task was to decide on dock for staging area. Once dock was selected, picker starts for picking in a set path. S-Shape path is followed in this study.

Data Analysis

Approach for Optimization

Distance optimization between any 2 bins/points within a warehouse was achieved by ants colonies optimization technique. These most optimized distances are stored in a distance matrix. Picklist of warehouse order was uploaded through an algorithm. Post upload, picklist should be cleaned for useful data. A customized list of bins was created that follows S shape strategy within an aisle. This customized list was given as input to custom sort to arrange the bins mentioned in picklist in ascending order. Once bins are arranged in ascending order, algorithm initiates from first row to pick particular bin location. Once this bin was picked then time taken to travel with this loaded pallet to all docks is calculated. Post all bins are picked, minimization function was implemented to get most optimize dock and time required for picking at optimize dock was calculated. Time required for picking a particular warehouse order at a most optimize dock is predicted (Annexure 1). This predicted standard time was compared with actual timings to get performance efficiency. Within a shift, all picklists were uploaded through this tool to get total standard time (Annexure 1) and productivity.

Creating a Distance matrix

The use of high-level vs low-level picking (van Gills, Caris, Ramaekers, & Braek, 2019) paved the way for identifying the feasible method to find the shortest distance between any 2 bins using ant colony optimization. Distance between all points were found out, next step was to create distance matrix of these distances. This file was saved in a directory where all master files were saved. All this distance values to be looked up while calculating time required for traveling (Annexure 1). Tecnomatix plant simulation was used to get shortest distance between any 2 points. Tecnomatix simulation was proposed by Monika Buckova, martin Krajcovic and Milan Edl (2017). It used genetic algorithm to find out shortest distance. Tecnomatix plant simulation 13 software displays models in 2D mode, 3D mode, or 2D/3D mode. The latest version is having 3D mode enabled.

Calculating Standard

Since entire model worked on factors/variable considered, its correct values selection is of most importance for accurately optimizing dock selection process and measuring productivity for a shift.

Standard human speed

Productivity and efficiency were impacted by average walking speed. If the assumed average walking speed is low, then it might lead to inflated productivity and efficiency figures. Correct assumption of human walking speed was necessary to estimate standard time required for order picking. Walking speed had been divided into 2 categories as per their speed ranges,

1. Average human walking speed when he/she walks freely with empty hand operated pallet truck
2. Average human walking speed when he/she carries loaded hand operated pallet truck.

Speed was observed on 7 pickers to arrive on a standard conclusion. Histogram of human walking speed when human walked freely is shown in Figure 2.

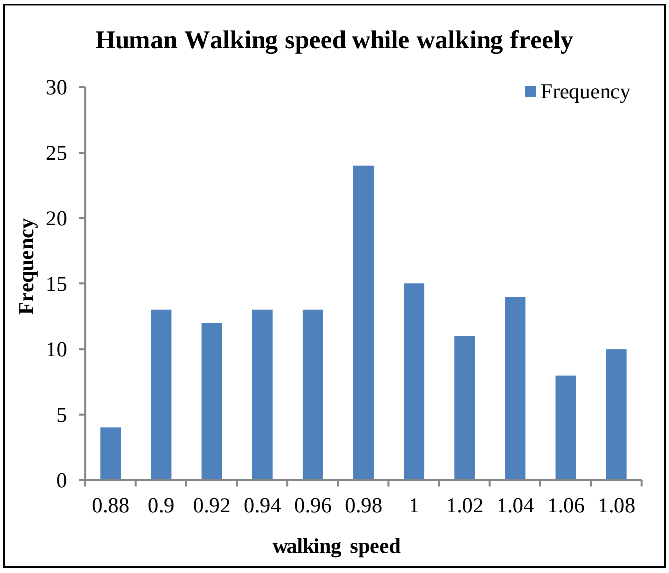


Figure 2: Distribution of human walking speed while walking freely

Time motion study was conducted in one warehouse for natural human walking speed. Total observation noted for human walking speed when picker walked freely is 137. All these 137 observations lie in the range of 0.87-1.08 meter per second. The mean and median for these observations was 0.98 meter per second and standard deviation was 0.059, Thus coefficient of variation was 0.06 which is far below 1 and approached 0. Thus, it was concluded that observations for freely walking human speed was not dispersed. On an average, every picker walks around 2 km every shift while picking. Total time difference in minutes is as follows

Total time taken for travelling 2 KM at lowest observed speed,

Time taken = 2/0.88*60 = 136.36 Min

Total time taken for travelling 2 KM at average observed speed,

Time taken = 2/0.98*60 = 122.5 Min

Total time taken for travelling 2 KM at highest observed speed,

Time taken = 2/1.08*60 = 111.5 Min

Since the difference between time taken for travelling 2 km with highest speed and average speed was 11 min for a shift, moreover due to fatigue, highest speed reduced as the day progress. Since difference was minimal and observation data was not dispersed to a large extent, 0.98 meter per second value was assumed for human walking speed with load of cases/bags. Speed distribution for a picker when he carried a fully loaded pallet is shown in Figure 3.

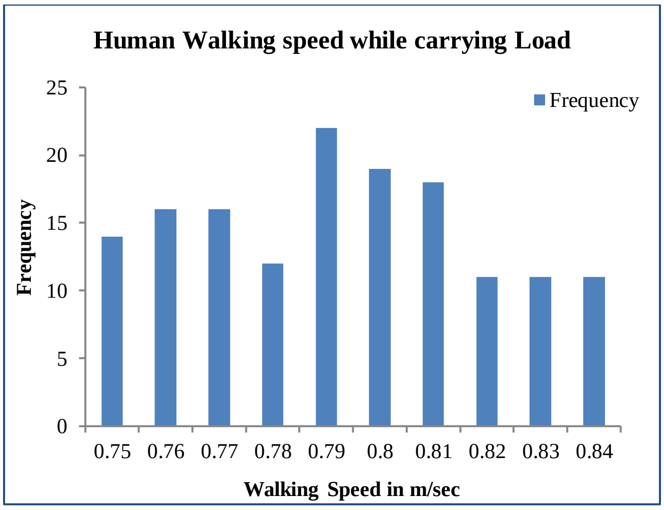


Figure 3: Distribution of human walking speed while carrying pallet

Total observation noted for human walking speed when picker carried load is 137. All these 137 observations lie in the range of 0.75 to 0.85 meter per second. The mean for this observation is 0.8 meter per second and standard deviation is 0.09, Thus coefficient of variation was 0.112 which is far below 1 and approached 0. Thus, observation for walking human speed is not dispersed and is uniform in nature. On an average every picker walks around 1.8 km every shift while picking. Total time difference in minutes is as follows,

Total time taken for travelling in a shift for 1.5 KM at lowest observed speed,

Time taken = 1.5/0.75*60 = 120 Min

Total time taken for travelling in a shift for 1.5 KM at average observed speed,

Time taken = 1.5/0.8*60 = 112.5 Min

Total time taken for travelling in a shift for 1.5 KM at highest observed speed,

Time taken = 1.5/0.85*60 = 106 Min

Thus, if average speed was considered then the best performer and average performer had a difference of only 6 mins in the entire shift of 9 hours. Since difference was minimal and observation data was not dispersed to a large extent, 0.8 meter per second value was assumed for human walking speed with load of cases/bags.

Standard cutoff for pallet utilization

An important parameter/variable named ‘Pallet fit’ was introduced which meant the number of cases/boxes needed to be stakced on a pallet for 100% pallet utilization. Thus, when boxes/cases of two or more SKU are formed on a same pallet then pallet fit ratio can be considered for deciding on cutoff for pallet break. Frequency of pallet fit is shown in Fig 4.

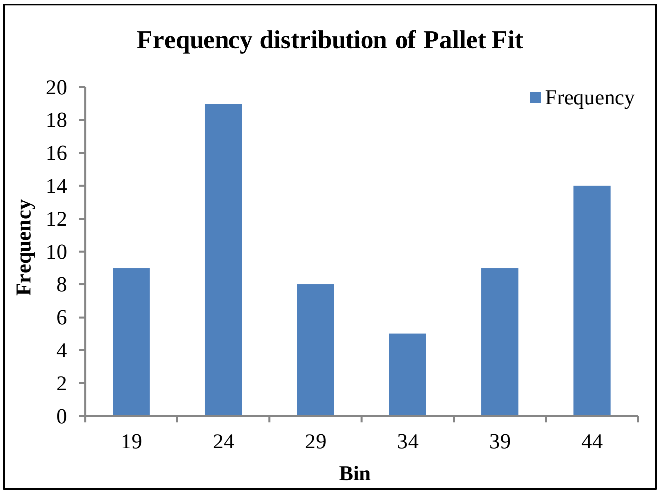


Figure 4: Pallet fit across a warehouse

A combination of 2,015 different SKU's was created. This SKU's were combined in such a manner that picker's visibility was not impacted by storage of cases/boxes. Distribution of pallet utilization cutoff with 100% visibility as shown in Figure 5.

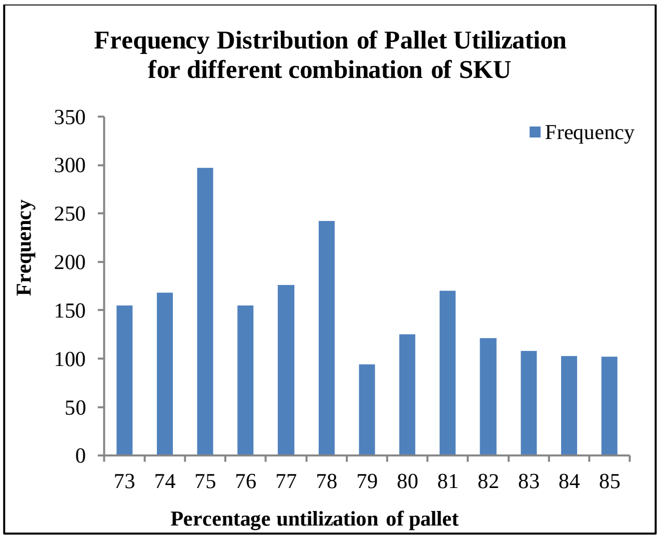


Figure 5: Cutoff pallet utilization for different combination of SKU

As seen from the above histogram, the dispersion was large ranging from 73% to 85%, Made it difficult to decide the cutoff. It can be seen from Figure 5, that the observations were not uniform. Thus, details of each cutoff percentage utilization were checked and it was observed that productivity increases by keeping a high pallet utilization of 85%. By observing all combinations at 85%, it was observed out that visibility might be impacted and thus effecting accuracy and damages but only 2.5% of all 2,015 combinations were observed to be having severe visibility issues if palled was formed till 85% utilization. Out of this 2.5%, 90% observations were observed where pallet was hardly loaded till 80% utilization because cases/boxes often failed stacking above 80% utilization. Visibility was good at 80% utilization of pallet. A lower cutoff along with higher cutoff of 85% was required and 80% was decided as lower cutoff. Thus, cutoff value for breaking a pallet was assumed 80-85% utilization value.

Standard time taken for pallet formation

Time required to pick a Case/box and keep it on a pallet was second most important factor/criteria in determining standard time required for a pallet formation. This factors hardly impacted Optimization of dock selection process but was of most importance for productivity measurement. Thus, correct assumption for time required for picking a case/box and keeping it on pallet needs to be considered for accurate time prediction. Similar to human walking speed, time taken for picking a case/box and to keep it on pallet varies as per SKU and its mass. Pallet formation time is proportional to product of weight and volume of a SKU. Larger SKU required more time compared to smaller SKU. It can be clearly seen than 80% of observations are below 12.5 seconds. Thus, decision on a single standard seconds for all SKU was a difficult task. Visual representation of pallet formation time is as shown in Figure 6.

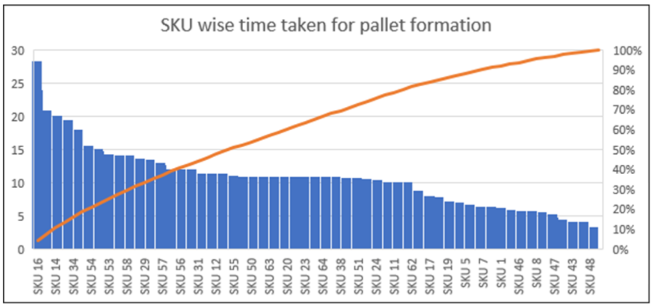


Figure 6: Standard seconds for pallet formation

Results of the descriptive statistics are presented in Table 3.

Table 3: Decriptive Statistics on pallet formation

Mean	10.909375
Standard Error	0.594984488
Median	10.9
Mode	10.9
Standard Deviation	4.759875907
Sample Variance	22.65641865
Kurtosis	2.528115836
Skewness	1.207665794
Range	25
Minimum	3.4
Maximum	28.4
Sum	698.2
Count	64
Largest (1)	28.4
Smallest (1)	3.4
Confidence Level (95.0%)	1.188981625
Mean	10.909375

As seen in Table 3, the coefficient of variation is 0.43 which indicated a relatively less dispersed sample. Also, median, mode and mean are same thus indicating normally distributed data. Skewness of 1.20 indicated sample is right skewed. Many observations lie above mean. Thus, with this descriptive result are not enough to conclude at any single value for picking a case/bags and form a pallet. So, picking order was observed from past historical data. A trend could be established in the presence of SKU in a customer order leading to clusters of SKU based on the picking were arrived at. 7 clusters were identified as presented in Table 4.

Table 4: standard time taken for pallet formation in Cluster

Cluster Name	Average Standard time for Pallet formation
Cluster 1	10.8
Cluster 2	11.0
Cluster 3	10.5
Cluster 4	11.9
Cluster 5	12.2
Cluster 6	12.6
Cluster 7	9.8

Now since all observations are within a limit of 9.8 to 12.6, It was concluded that a standard second of 11.2 seconds should be used as a standard second for picking a case/box and forming a pallet out of it.

Findings And Results

Prior to developing this tool, it was found that in 33% of cases dock selected for staging was least optimize and thus impacted negatively in warehouse productivity. Impact of the studied model on productivity and efficiency are presented in Table 5.

Table 5: Improvement in productivity

	Prior implementing tool	Post implementing tool
Productivity for each picker in a shift	4 picking order per shift	5 picking order per shift

It can be seen that individual picker productivity increased by 25% post implementing the tool. The average of 1 week was considered for deriving the final conclusion. Post implementing, few manpower shortcomings were also identified. Total 100 picking orders were studied post validating the tool, a Total of 22 picking orders were observed with low efficiency/productivity. Actual time taken for picking by these 22 picking order were 25-30% higher than standard time required. On root cause analysis, it was identified that pickers were lethargic. Details of picker with less efficiency is as displayed in Table 6.

Table 6: Pickers performance efficiency

Picker name	Frequency
Ganesh	7
Ajay	6
Rohan	3
Sahil	3
Suraj	2
Mohit	1

Except Ganesh and Ajay, all others were new pickers and thus can be considered for low efficiency but Ganesh and Ajay were old guards and still accounted for around 13 out of 22 i.e. 59 %. Thus, the remaining pickers were retrained.

Conclusion

VBA code based dynamic model was identified which could optimize productivity post warehouse layout design. This VBA enabled MS-Excel model could recommend most optimize dock for every warehouse order, depending upon type of warehouse order. The main aim of this study was to optimize dock selection process and measure productivity of manpower. Output of this study is a dynamic algorithm/model that predicts standard time required for picking a warehouse order in a warehouse. This can help manpower planners to plan manpower according to Sales forecast for a particular facility location. Warehouse manager can adjust picker numbers as per marketing and sales plan with increased productivity of 25%. This study also helped manager to identify their capacity pipeline and execute warehouse orders in case of any shocks from demand and supply side.

Limitation and Scope for further research

This study uses a case of a warehouse to analyse the question understudy. The limitations of the case study method of study are applicable to this study. However, given the exploratory nature of this study, the case study was found to be appropriate. Similar models could be created for other activities within a warehouse. Picking hit ratio should be added as a variable. Human behavioral factors like tardiness and fatigue were left and could be considered in future research. Further research activities could focus on (1) a structured and systematic review of the literature on order picking coupled with the use of technology (2) high level picking activity and predicting or modeling picking hit ratio (3) granularity of model could be increased with human behavioral factors/variables and real time data through use of IOT.

References

[1] Aboelfotoh, A., Singh, M., & Suer, G. (2019). Order Batching Optimization for Warehouses with Cluster-Picking. *Procedia Manufacturing*, *39*, 1464-1473.

[2] Arabani, A. B., Ghomi, S. F., & Zandieh, M. (2011). Meta-heuristics implementation for scheduling of trucks in a cross-docking system with temporary storage. *Expert systems with Applications*, *38*(3), 1964-1979.

[3] Ardjmand, E., Ghalehkhondabi, I., Young II, W. A., Sadeghi, A., Sinaki, R. Y., & Weckman, G. R. (2020). A Hybrid Artificial Neural Network, Genetic Algorithm and Column Generation Heuristic for Minimizing Makespan in Manual Order Picking Operations. *Expert Systems with Applications*, 113566.

[4] Ardjmand, E., Shakeri, H., Singh, M., & Bajgiran, O. S. (2018). Minimizing order picking makespan with multiple pickers in a wave picking warehouse. *International Journal of Production Economics*, *206*, 169-183.

[5] Ashayeri, J., & Gelders, L. F. (1985). Warehouse design optimization. *European Journal of Operational Research*, *21*(3), 285-294.

[6] Bastien, G. J., Willems, P. A., Schepens, B., & Heglund, N. C. (2005). Effect of load and speed on the energetic cost of human walking. *European journal of applied physiology*, *94*(1-2), 76-83.

[7] Berglund, P., & Batta, R. (2012). Optimal placement of warehouse cross-aisles in a picker-to-part warehouse with class-based storage. *IIE Transactions*, *44*(2), 107-120.

[8] Bottani, E., Cecconi, M., Vignali, G., & Montanari, R. (2012). Optimisation of storage allocation in order picking operations through a genetic algorithm. *International Journal of Logistics Research and Applications*, *15*(2), 127-146.

[9] Bottani, E., Montanari, R., & Rinaldi, M. (2019). Development and testing of software tool for warehouse design and picking optimisation. *International Journal of Management and Decision Making*, *18*(2), 119-150.

[10] Bottani, E., Montanari, R., Rinaldi, M., & Vignali, G. (2015). Intelligent algorithms for warehouse management. In *Intelligent Techniques in Engineering Management* (pp. 645-667). Springer, Cham.

[11] Bottani, E., Volpi, A., & Montanari, R. (2019). Design and optimization of order picking systems: An integrated procedure and two case studies. *Computers & Industrial Engineering*, *137*, 106035.

[12] Boysen, N., Fliedner, M., & Scholl, A. (2010). Scheduling inbound and outbound

trucks at cross docking terminals. *OR spectrum*, *32*(1), 135-161.

[13] Brezina Jr, I., & Čičková, Z. (2011). Solving the travelling salesman problem using the ant colony optimization. *Management Information Systems*, *6*(4), 10-14.

[14] Bučková, M., Krajčovič, M., & Edl, M. (2017). Computer simulation and optimization of transport distances of order picking processes. *Procedia engineering*, *192*, 69-74.

[15] Bukchin, Y., Khmelnitsky, E., & Yakuel, P. (2012). Optimizing a dynamic order-picking process. *European Journal of Operational Research*, *219*(2), 335-346.

[16] Caron, F., Marchet, G., & Perego, A. (1998). Routing policies and COI-based storage policies in picker-to-part systems. *International journal of production research*, *36*(3), 713-732.

[17] Çelik, M., & Süral, H. (2019). Order picking in parallel-aisle warehouses with multiple blocks: complexity and a graph theory-based heuristic. *International Journal of Production Research*, *57*(3), 888-906.

[18] CHANG, F. L., LIU, Z. X., Zheng, X. I. N., & LIU, D. D. (2007). Research on order picking optimization problem of automated warehouse. *Systems Engineering-Theory & Practice*, *27*(2), 139-143.

[19] De Jong, J., & Wiering, M. A. (2001). Multiple Ant Colony Systems for the Busstop Allocation Problem. In *Proceedings of the Thirteenth Belgium-Netherlands Conference on Artificial Intelligence* (pp. 141-148).

[20] De Koster, R., & Van Der Poort, E. (1998). Routing orderpickers in a warehouse: a comparison between optimal and heuristic solutions. *IIE transactions*, *30*(5), 469-480.

[21] De Santis, R., Montanari, R., Vignali, G., & Bottani, E. (2018). An adapted ant colony optimization algorithm for the minimization of the travel distance of pickers in manual warehouses. *European Journal of Operational Research*, *267*(1), 120-137.

[22] Dorigo, M., Colorni, A., & Maniezzo, V. (1991). Distributed optimization by ant colonies.

[23] Dorigo, M., Maniezzo, V., & Colorni, A. (1996). Ant system: optimization by a colony of cooperating agents. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, *26*(1), 29-41.

[24] Forouharfard, S., & Zandieh, M. (2010). An imperialist competitive algorithm to schedule of receiving and shipping trucks in cross-docking systems. *The International Journal of Advanced Manufacturing Technology*, *51*(9-12), 1179-1193.

[25] Hougardy, S. (2010). The Floyd–Warshall algorithm on graphs with negative cycles. *Information Processing Letters*, *110*(8-9), 279-281.

[26] Huurne, T. S. (2016). *Analysing and improving the performance of the pallet break down process by SUEZ for Scania* (Master's thesis, University of Twente).

[27] Hwang, H., Hui Oh, Y., & Nam Cha, C. (2003). A stock location rule for a low level picker-to-part system. *Engineering Optimization*, *35*(3), 285-295.

[28] Jarvis, J. M., & McDowell, E. D. (1991). Optimal product layout in an order picking warehouse. *IIE transactions*, *23*(1), 93-102.

[29] Klodawski, M., Jachimowski, R., Jacyna-Golda, I., & Izdebski, M. (2018). Simulation analysis of order picking efficiency with congestion situations. *International Journal of Simulation Modelling*, *17*(3), 431-443.

[30] Kuo, R. J., Kuo, P. H., Chen, Y. R., & Zulvia, F. E. (2016). Application of metaheuristics-based clustering algorithm to item assignment in a synchronized zone order picking system. *Applied Soft Computing*, *46*, 143-150.

[31] Le-Duc*, T., & De Koster, R. M. B. (2005). Travel distance estimation and storage zone optimization in a 2-block class-based storage strategy warehouse. *International Journal of Production Research*, *43*(17), 3561-3581.

[32] Liao, T. W., Egbelu, P. J., & Chang, P. C. (2013). Simultaneous dock assignment and sequencing of inbound trucks under a fixed outbound truck schedule in multi-door cross docking operations. *International Journal of Production Economics*, *141*(1), 212-229.

[33] Lu, W., McFarlane, D., Giannikas, V., & Zhang, Q. (2016). An algorithm for dynamic order-picking in warehouse operations. *European Journal of Operational Research*, *248*(1), 107-122.

[34] Lucic, P., & Teodorovic, D. (2002, November). Transportation modeling: an

artificial life approach. In *14th IEEE International Conference on Tools with Artificial Intelligence, 2002.(ICTAI 2002). Proceedings.* (pp. 216-223). IEEE.

[35] Maknoon, M. Y., & Baptiste, P. (2009). Cross-docking: increasing platform efficiency by sequencing incoming and outgoing semi-trailers. *International Journal of Logistics: Research and Applications*, *12*(4), 249-261.

[36] Manzini, R., Accorsi, R., Gamberi, M., & Penazzi, S. (2015). Modeling class-based storage assignment over life cycle picking patterns. *International Journal of Production Economics*, *170*, 790-800.

[37] Mariano, C. E., & Morales, E. M. (1999, July). MOAQ an ant-Q algorithm for multiple objective optimization problems. In *Proceedings of the 1st Annual Conference on Genetic and Evolutionary Computation-Volume 1* (pp. 894-901).

[38] Matusiak, M., de Koster, R., Kroon, L., & Saarinen, J. (2014). A fast simulated annealing method for batching precedence-constrained customer orders in a warehouse. *European Journal of Operational Research*, *236*(3), 968-977.

[39] Önüt, S., Tuzkaya, U. R., & Doğaç, B. (2008). A particle swarm optimization algorithm for the multiple-level warehouse layout design problem. *Computers & Industrial Engineering*, *54*(4), 783-799.

[40] Rakesh, V., & Adil, G. K. (2015). Layout optimization of a three dimensional order picking warehouse. *IFAC-PapersOnLine*, *48*(3), 1155-1160.

[41] Ratliff, H. D., & Rosenthal, A. S. (1983). Order-picking in a rectangular warehouse: a solvable case of the traveling salesman problem. *Operations research*, *31*(3), 507-521.

[42] Richards, G. (2017). *Warehouse management: a complete guide to improving efficiency and minimizing costs in the modern warehouse*. Kogan Page Publishers.

[43] Roodbergen, K. J., Vis, I. F., & Taylor Jr, G. D. (2015). Simultaneous determination of warehouse layout and control policies. *International Journal of Production Research*, *53*(11), 3306-3326.

[44] Scholz, A. (2016). *An Exact Solution Approach to the Single-Picker Routing Problem in Warehouses with an Arbitrary Block Layout*. Otto-von-Guericke-Universität Magdeburg, Fakultät für Wirtschaftswissenschaft, Der Dekan.

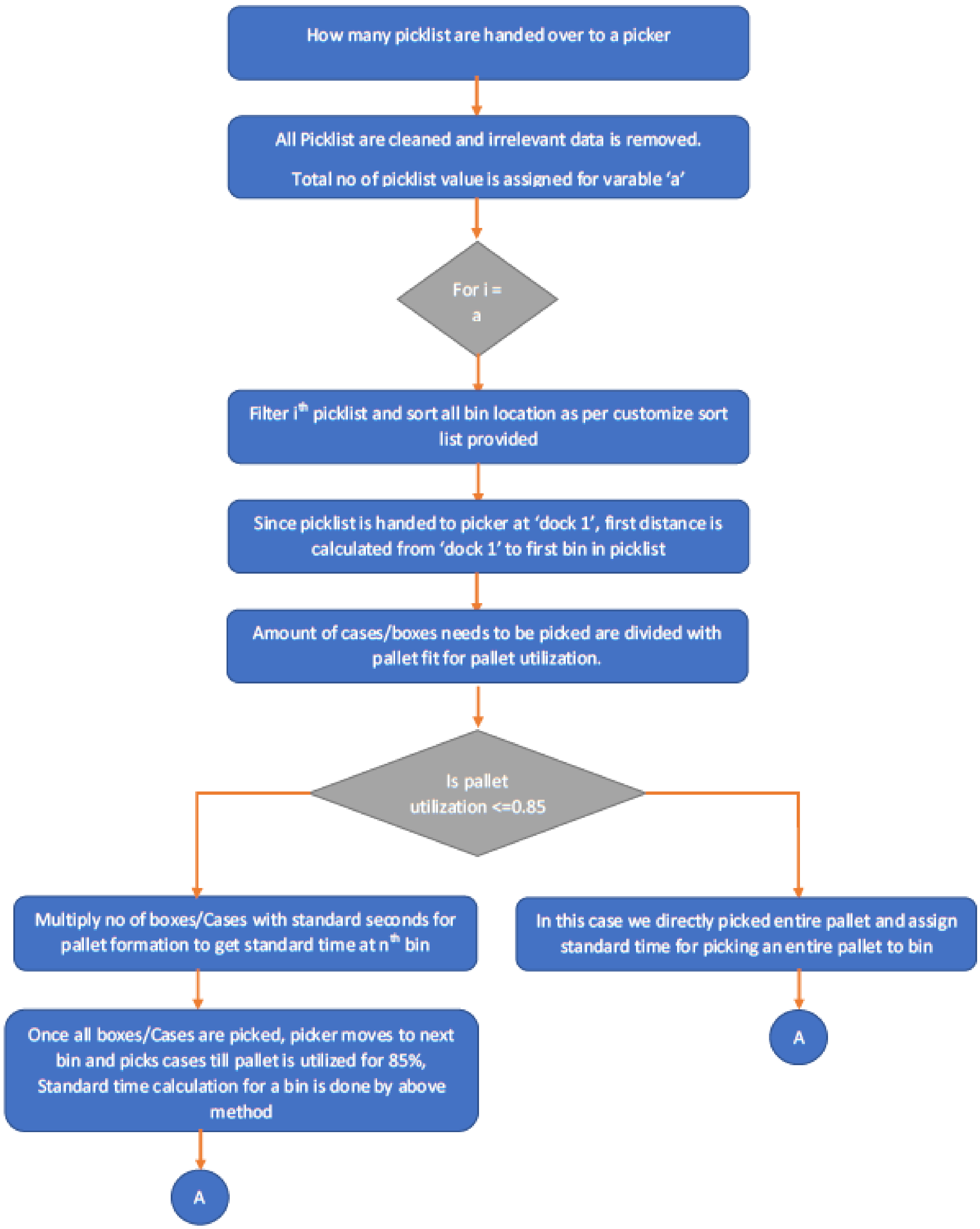
[45] Shtovba, S. D. (2005). Ant algorithms: theory and applications. *Programming and Computer Software*, *31*(4), 167-178.

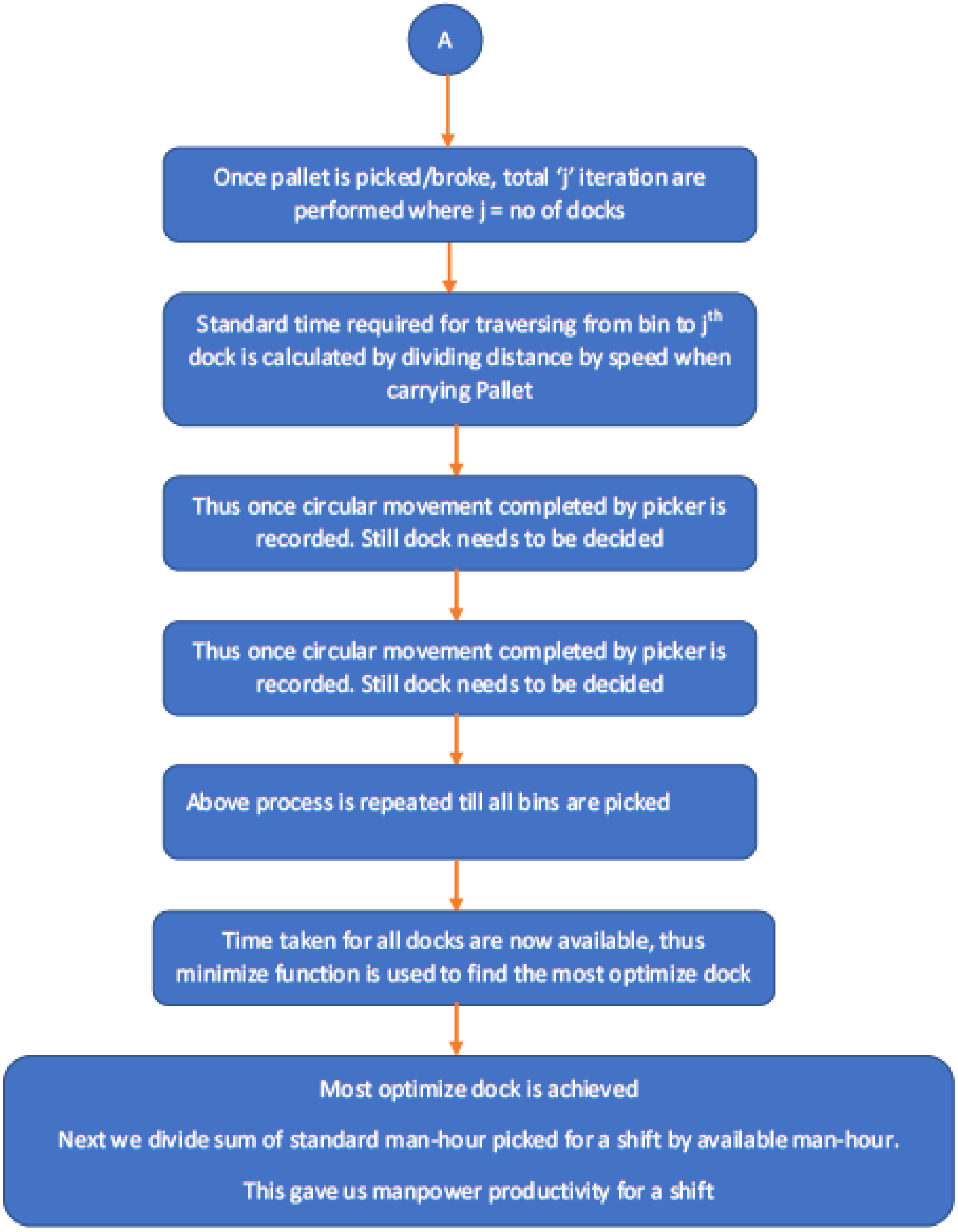
[46] Soltani, R., & Sadjadi, S. J. (2010). Scheduling trucks in cross-docking systems: A robust meta-heuristics approach. *Transportation Research Part E: Logistics and Transportation Review*, *46*(5), 650-666.

[47] Stützle, T., & Hoos, H. H. (2000). MAX–MIN ant system. *Future generation computer systems*, *16*(8), 889-914.

[48] Vahdani, B., & Zandieh, M. (2010). Scheduling trucks in cross-docking systems: Robust meta-heuristics. *Computers & Industrial Engineering*, *58*(1), 12-24.

[49] Yu, W., & Egbelu, P. J. (2008). Scheduling of inbound and outbound trucks in cross docking systems with temporary storage. *European journal of operational research*, *184*(1), 377-396.


How many picklist are handed over to a picker
All Picklist are cleaned and irrelevant data is removed.
Total no of picklist value is assigned for varable 'a'
For i = a
Filter i th picklist and sort all bin location as per customize sort list provided
Since picklist is handed to picker at 'dock 1', first distance is calculated from 'dock 1' to first bin in picklist
Amount of cases/boxes needs to be picked are divided with pallet fit for pallet utilization.
Is pallet utilization <=0.85
Multiply no of boxes/Cases with standard seconds for pallet formation to get standard time at n th bin
In this case we directly picked entire pallet and assign standard time for picking an entire pallet to bin
Once all boxes/Cases are picked, picker moves to next bin and picks cases till pallet is utilized for 85%, Standard time calculation for a bin is done by above method
A
A


A
Once pallet is picked/broke, total 'j' iteration are performed where j = no of docks
Standard time required for traversing from bin to jth dock is calculated by dividing distance by speed when carrying Pallet
Thus once circular movement completed by picker is recorded. Still dock needs to be decided
Thus once circular movement completed by picker is recorded. Still dock needs to be decided
Above process is repeated till all bins are picked
Time taken for all docks are now available, thus minimize function is used to find the most optimize dock
Most optimize dock is achieved
Next we divide sum of standard man-hour picked for a shift by available man-hour.
This gave us manpower productivity for a shift